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Optimal Delay-Bounded Scheduling in Wireless Sensor Networks

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Abstract: We investigate the problem of prolonging network life time considering an upper bound on the tolerable delay. According to the characteristics of the application in-hand, we put a constraint on the number of active nodes. In the proposed approach a mobile sink is taken advantage. The problem is formulated as a Linear Programming optimization using which both sink's mobility pattern and the optimum flow assignment are obtained. Using the proposed formulation, a (1-ε) optimal solution (i.e., the network lifetime is at least (1-ε) of the optimal network lifetime) is obtained. Numerical results indicates that by jointly considering the QoS requirements, routing, scheduling and sink mobility the network lifetime can be improved significantly.

Keywords: Delay, Network Lifetime, Approximation, Linear Programming, QoS

I. Introduction

Wireless sensor networks (WSNs) consisting of a large number of wireless sensor nodes which are spatially distributed in a designated region. Sensor nodes provide a distributed environment sensing for remote or inaccessible areas. In fact, each sensor node can gather information from its surrounding area.

The collected data will be delivered to the base station, which is also known as a sink node, generally via multi-hop communication. The sensor nodes are typically expected to operate with batteries while battery replacement is an inconvenient and expensive task and usually is not possible. As a consequence, efficient energy utilization for prolonging the network lifetime has been the focus of much of the researches on the WSNs [1].

Sensors are typically deployed densely in the monitoring region. Due to spatial redundancy of sensor nodes and wide sensing range, same part of the monitoring field may be sensed by different sensors simultaneously.

On one hand, in critical application such as battlefield surveillance, overlapped monitoring makes the collected data more reliable and because of that all sensors are required to be in active move.

On the other hand, in some applications where network lifetime prolonging is more critical than providing accurate information, network lifetime can be prolonged by using only a subset of sensors at each point of time. For instance, in temperature sensing applications, sensing the temperature of a point could be adequate to its surrounding area. Thus, putting a subset of sensors into sleep mode to save energy is an efficient approach for network lifetime elongation in these kinds of applications.

Developing a real-time applications over WSNs should consider not only resource constrains, but also providing a certain delay guarantee for data delivery.

In contrast with the real-time applications, in delay-tolerant applications, employing data buffering methods is an efficient way for prolonging network lifetime. In other words, in applications which can tolerate a degree of delay in delivering the data packets to the sink node, each sensor node can postponed its data transmission for a while. Especially when a mobile data gathering is used, each sensor node can postponed its data transmission until the sink node is closed enough.

In fact, WSNs are quite useful in many applications such as battlefield surveillance, medical diagnostics, environmental and habitat monitoring, each having specific requirements. In order to deliver the collected data with different requirements in highly energy constrained WSNs, application QoS provisioning becomes unavoidable. Actually, QoS support mechanisms brings the ability of giving different priorities to varied applications according to their requirements.

QoS provisioning are utilized to manage the resource sharing according to the application-specific requirements. For the purpose of application differentiation, we focus on two QoS parameters listed as follow:

1- *Accuracy*: what percent of sensor nodes are needed to be in active mode at each point of time to meet the application accuracy level?

2- *Upper-bound on tolerable delay*: How much data delivery delay is tolerable based on the application in-hand?

The question is to find a routing paths meeting the minimum application-specific QoS requirements. In practice, longevity of the network lifetime is desired in many applications.

Due to the limited battery power of the sensor nodes, it is extremely important that the routing be energy efficient, which aims at increasing the network lifetime. Routing protocols aiming to save energy in WSNs mainly focus on the sensor nodes, whereas a recent trend indicates a focus shift to the behavior of sink node, which can be employed to further improve the lifetime of WSNs. In fact, using a mobile sink or relay node can improve the network lifetime significantly [2-4].

The main reason for the improvement brought by the sink mobility approaches is the typical many-to-one traffic pattern in WSNs which is also known as convergecast. Such a flow pattern imposes a heavy forwarding load on the nodes close to the sink node. As a result, sensors which are closer to the sink node tend to run out of energy faster than the other ones.

While no energy-conserving protocol alleviates such a load, moving the sink node can distribute the role of bottleneck nodes over time. Furthermore, mobile sinks may improve the network connectivity by enabling the retrieval from several isolated parts of the WSNs.

In this paper, we exploit sink mobility to maximize the network lifetime for a WSN with a known application QoS requirements. For $(1 - \varepsilon)$ optimality, the infinite possible locations for sink mobility reduced to a finite set of locations.

Our main contribution is that the proposed formulation fulfill the application QoS requirements, and in addition, it results a $(1 - \varepsilon)$ optimal solution. The problem is formulated based on linear programming optimization subjected to maximize the network lifetime while meeting application QoS requirements are guaranteed.

The rest of this paper is organized as follows: In Section II, we have given a brief overview of the state-of-the-art on related lifetime maximization problems. In Section III, we gave a problem definition and statement in detail. Proposed method is presented in section IV. Performance evaluation and simulation results are shown in section V. In section VI, the paper ends with a concluding epilogue along with a hint on future works conceivable in this area.

II. Related Works

In this section, we present a comprehensive review on the related lifetime maximization problems that have been published in the literature.

Optimal sink node placement has been an active area of research for network lifetime maximization in many recent studies (see, e.g, [1-3]). The focus was mainly devoted to determination of the optimal sink location and sensor-to-sink information flow routes. However, network lifetime can be further improved by using a mobile sink [2-6].

In [6], Wanget et al tried to maximize the network lifetime by considering a pre-determined routing paths. In fact, they proposed a new formulation for determining the sink sojourn time in order to maximize the network lifetime. This differs from our proposed method in that we jointly consider routing, QoS and sink mobility.

However, in [8] Papadimitriou and Georgiadis extend the formulation used in [6] by jointly considering sink mobility and routing to maximize the network lifetime. The sink node is however confined to a limiter set of location (i.e., the sink node can just move between a predefined set of anchor points).

In [7] authors investigated on the joint sink mobility and routing to improve the network lifetime. Limited set of locations are used as the sink anchor points. They proved the superiority of mobile sink node over static sink node in the case that the sinks are constrained to where the nodes are (i.e., the set of sensor locations selected as possible anchor points for the sink mobility). They proposed a linear programming formulation in which the sink sojourn time and corresponding routing are determined in order to maximize the network lifetime.

However, they did not considered the transmission distance in the transmission energy consumption model whereas the recent studies showed that tuning the transmission power according the transmission distance can improve the network lifetime [10].

Besides, their formulation is not applicable for unconstrained sink mobility. An extension of [7] is presented recently in [9] where an approximation method used to develop the constrained sink mobility into unconstrained sink mobility. However, they did not assumed QoS requirements in their formulation.

Distributed sink mobility and routing approach proposed in [11] in which the sink node can move between a limited and predefined set of locations. They proposed a linear programming formulation for joint sink mobility and routing in order to maximize the network lifetime. Lagrangian [19] and subgradient [20] method used to solve the problem in distributed manner. However, they did not consider the energy consumed in a sensor node for data reception. Their

proposed method consists of two different phases. Initialization phase requires co-operation between sensor nodes to achieve a near optimal solution. Besides, in routing phase, the solution found in the initialization phase is used to forward the data packets toward the sink node. However, low convergence speed of lagrangian and subgradient method cause energy depletion of some sensor in the initialization phase.

Same as [11], in another contribution [12] authors investigated on the distributed algorithm for mobile data gathering in wireless sensor networks. They employed anchor based mobile data gathering to maximize the network utility under the constrained and guaranteed network lifetime.

In fact, the only parameter assumed as QoS is the network lifetime which is guaranteed to achieved while the network utility is maximized. They used Lagrangian heuristic along with subgradient method to solve the problem in distributed manner. However, they did not assumed energy consumed in a sensor node for data reception. Besides, their proposed method has low convergence speed.

There were some efforts on lifetime maximization problem by using mobile sink in delay tolerant applications. [13-15].Yun and Xia[13] exploited the sink mobility in WSNs where undelaying applications tolerate delayed information delivery to the sink node.

They proposed a new formulation in which each sensor node sends data to the sink when the mobile sink is within a given distance of the sensor. In fact, at each point of time, only sensors which their distance to the sink node is less or equal than specific value should send their data to the sink node. Obviously, using this approach cannot guarantee the end to end delay in data delivery. In contrast with [13], in our proposed approach, end to end delay is guaranteed to be less or equal than specific value.

In [14] authors studied on joint optimization problem consisting of trajectory finding and sojourn time scheduling with an aim to maximize the network throughput. They assumed a set of potential sojourn locations for the mobile sink node and employed a heuristic method to find out the sink sojourn time and routing at each location.

III. SYSTEM MODEL

We model a WSN as digraph $G = (V, E)$ where $|V| = n$ indicates the sensor nodes and $\exists(i, j) \in E$ if and only if node j is located within the transmission range of node i.

Let S represent the sink node which harvest data from the WSN. All sensor nodes are stationary while the sink node can change its location from time to time with a negligible traveling time between two locations. Each sensor node i which is located at (x_i, y_i) has E_0 Joules of energy as initial energy and generates data with the rate of r.

The generated data by each sensor node should be transmitted to the sink node S via a single hop or a multi-hop communication. *Table I* lists the notation used in this paper.

We assumed that each sensor node can control its transmission range.

Suppose node i and j while d shows the Euclidean distance between node i and j. Let E_{ij}^t denotes the energy consumed for sending a bit of data from node i to node j. Then the transmission energy cost is modeled by

$$E_{ij}^t = e_t + \beta . d_{ij}^{\alpha} \qquad (1)$$

Where e_t and β are constant coefficients and α is path loss parameter which takes value between 2 and 4.

Let E_r denotes the energy consumed for receiving a bit of data. Since the sender node controls its transmission power level, the receiver node consumes a constant amount of energy for receiving a bit of data.

We assumed that the sink node can change its location from time to time with negligible traveling time. Since a mobile sink node is employed, in delay-tolerance applications each sensor node can postpone its data transmission until the sink node stops at the most favorable location for extending the network lifetime.

Each sensor senses its surrounding area periodically and generates data packets with a certain rate. Each sensor has limited amount of memory which can be employed for buffering data packets. In other words, each sensor is able to gather data form its surrounding environment and buffer data by using its limited memory and send them to the sink node in a certain period of times.

Based on the application, each node can postpone its data transmission for a certain amount of time. Let D indicates the maximum tolerable delay in seconds.

By using a FIFO queuing policy for selecting data packets from the memory buffer, for sensor node i which generates data with the rate of r bits per second and has M bits of memory for data buffering, maximum data delay would be $\frac{M}{r}$ second.

Note that we ignore transmission and propagation delay. Besides, we assumed that each sensor node use its buffer memory to store its own data packet.

As a consequence, by controlling the buffer queue length, one can insure end to end data delivery delay

Table I. notations

V	Set of sensors
S	Sink node
E	Set of wireless links
α	Path loss parameter
E_{ij}^{t}	Energy consumed for sending a bit of data from sensor *i* to sensor *j*.
E_r	Energy consumed for receiving a bit of data.
E_0	Sensor initial energy.
r	Data generation rate
O_A	Center of SED
R_A	Radius of SED
D_{iS}^{min}	Minimum distance from sensor node *i* to the sink node
D_{iS}^{max}	Maximum distance from sensor node *i* to the sink node
D_{iO_A}	Euclidean distance from sensor node *i* to the center of SED
$E\_min_{iS}^{t}$	Minimum Energy required for sending a bit of data from sensor node *i* to the sink node
$E\_max_{iS}^{t}$	Maximum Energy required for sending a bit of data from sensor node *i* to the sink node
$E_{iS}^{t}[j]$	Transmission energy cost for sending a bit of data from sensor node *i* to the sink node which is located at subarea *j*
H_i	Maximum number of circles required for sensor node *i* to cover SED completely.
ε	Approximation error (ε>0)
A_m	Subarea *m*
p_m	Point located at A_m
T	Network lifetime
D	Endurable delay
ρ	Accuracy parameter
F_{ij}^{k}	Amount of data flow send by node *i* to node *j* during *k*-th epoch.
${B_{input}}_i^k$	Amount of data which node *i* stores at its own data buffer during *k*-th epoch
${B_{output}}_i^k$	Amount of data which node *i* sends from its own data buffer during *k*-th epoch
${B_{length}}_i^k$	Queue buffer length of sensor *i* during *k*-th epoch
${B_{length}}_i^0$	Queue buffer length of sensor *i* at the system initialization

We now argue on how to move the sink node with (1 − ε) optimal network lifetime guarantee. Denote A the movement region for the sink node, which can be narrowed down to the smallest enclosing disk (SED) for all sensor nodes, i.e., smallest circular area that covers all the nodes in the network [15]. Note that for a given WSN, the SED can be found in polynomial time [16]. Denote O_A and R_A as the origin and radius of SED A respectively. Let D_{iS}^{min} and D_{iS}^{max} the minimum and maximum Euclidean distance from sensor i to sink node S. Since the movement region for the sink node S is within SED A, we have:

$$D_{iS}^{min} = 0 \qquad (2)$$
$$D_{iS}^{max} = D_{iO_A} + R_A \qquad (3)$$

Corresponding to D_{iS}^{min} and D_{iS}^{max}, denote $E\_min_{iS}^{t}$ and $E\_max_{iS}^{t}$ the minimum and maximum transmission energy cost between sensor node i to the sink node S. Then by (1) ,(2) and (3), we have:

$$E\_min_{iS}^{t} = e_t \qquad (4)$$
$$E\_max_{iS}^{t} = e_t + \beta(D_{iS}^{max})^{\alpha} = e_t + \beta(D_{iO_A} + R_A)^{\alpha} \qquad (5)$$

Obviously, the Euclidean distance between sender and receiver affects the transmission energy cost. Thus, to achieve (1 − ε) optimal network lifetime, we divide SED into finite number of subareas while the Euclidean distance from each subarea to sensor i meeting some tight bounds. For each sensor $\in V$, each subarea j is associate with transmission energy cost $E_{iS}^{t}[j]$ which shows the transmission energy cost for sending a bit of data to the sink node S which is located at the subarea j.

In fact, discrete energy cost is used based on geometric sequence [18]. Specifically, by drawing a sequence of circles centered at node i, each with increasing distance $d[1], d[2], \dots, d[H_i]$ corresponding to transmission energy cost $E_{iS}^{t}[1], E_{iS}^{t}[2], \dots, E_{iS}^{t}[H_i]$ which are defined based on the following geometric sequence:

$$E_{iS}^{t}[h] = E\_min_{iS}^{t}(1+\varepsilon)^{\alpha} = e_t(1+\varepsilon)^{\alpha} \quad 1 \le h \le H_i \qquad (6)$$

In fact, $E_{iS}^{t}[1], E_{iS}^{t}[2], \dots, E_{iS}^{t}[H_i]$ is geometric sequence with the factor of (1+ε).

For each sensor i, the number of required circles to cover A completely (i.e., H_i) can be determined by having the last circle in the sequence which :

$$E_{iS}^{t}[H_i] \ge E\_max_{iS}^{t} \qquad (7)$$

Thus H_i can be determined as follows:

$$H_i = \left\lceil \frac{ln(E\_max_{iS}^t / E\_min_{iS}^t)}{ln(1+\varepsilon)} \right\rceil = \left\lceil \frac{ln(1 + \frac{\beta}{e^t}(D_{io_A} + R_A)^\alpha)}{ln(1+\varepsilon)} \right\rceil = O\left(\left\lceil \frac{1}{\varepsilon} \right\rceil\right) = O(\frac{1}{\varepsilon}) \quad (8)$$

Where the third one hold by $\ln(1+\varepsilon) \approx \varepsilon$ for small ε and $1 + \frac{\beta}{e^t}(D_{io_A} + R_A)^\alpha$ is a constant. For each sensor node i, drawing the circles according to the above procedure results H_i non-overlapping rings each has radios of $d[j](1 \leq j \leq H_i)$. By locating the base station between *(j-1)*–th circle and *j*–th circle, the transmission energy cost for sending a bit of data from sensor node *i* to sink node *S* would be:

$$E_{iS}^t[h-1] \leq E_{iS}^t \leq E_{iS}^t[h] \quad (9)$$

While we assume that $E_{iS}^t[0] = E\_min_{iS}^t = e_t$. Because of $\frac{E_{iS}^t[h]}{E_{iS}^t[h-1]} = 1 + \varepsilon$ based on (6), we can claim that these two bound for E_{iS}^t are very tigh.

By performing the above procedures for all sensor nodes, the intersecting circles will divide disk A into a finite number of subareas with irregular shapes. Note that for each sensor node *i*, any subarea A_m is located within circle centered at node *i*. Denote the index of this circle as $h_i(A_m)$. So, for a sink node *S* which is located at any point within A_m , transmission energy cost would be:

$$E_{iS}^t \leq E_{iS}^t[h_i(A_m)] \quad (10)$$

So each subarea A_m assumed as point p_m where the transmission energy cost for sending a bit of data from sensor *i* to the sink node *S* located at p_m assume as follows:

$$E_{iS}^t = E_{iS}^t[h_i(A_m)] \quad (11)$$

For unconstrained sink mobility model we can assume the SED as a set of finite points.

The question is to find a sink sojourn time at each point p_m and corresponding data routing solution which maximize the network lifetime.

IV. PROBLEM STATEMENT AND FORMULATION

We assume a set of sensors which distributed randomly in a monitoring region. We assume that the location of sensor nodes and sink nodes are known at the system startup. If cat we can used GPS based or GPS less localization method to achieve the sensors location.

Sensor nodes gather data from monitoring region while the sink node changes its location from time to time in order to gather data from sensor nodes.

Based on the predefined QoS requirements, at least ρ percent of all sensors should generate data with the rate of r bit per second at each point of time while each sensor node can postpone its data transmission for D seconds

Based on the sink mobility model, the sink node can move around the SED while the SED is divided into a finite number of subareas.

Since the transmission energy cost for each subarea is constant for each sensor node, we assume each subarea as point. The sink node can stop at each point for a certain amount of time.

Although the network lifetime can be defined in many ways, we adopt the time until the first sensor node exhausts its energy as network lifetime, which is a widely used.

We denote the network lifetime by T and use t_k to indicate timespan the for the *k*-th epoch. By changing the sink node location, a new epoch began.

We denote the total information flow from sensor node *i* to sensor node *j* during the *k*-th epoch by F_{ij}^k. Based on the problem definition, for a given value of ρ, at least ρ% of all sensors should generate data by the rate of r at each point of time. Since we assumed that based on the application in-hand, not all sensors are needed to be in active mode, q'_{ik} used to indicate total information flow which sensor *i* does not send generate during the *k*-the epoch.

However, for delay-tolerance application, the memory buffer can be employed for storing data packets.

Let ${B_{input}}_i^k$ indicated the total information flow which sensor stores at its own buffer memory during the *k*-th epoch and ${B_{output}}_i^k$ as total information flow which sensor sends from its own buffer during the *k*-th epoch.

Without loss of generality, we assume that the sink node dwells at the *k*-th subarea during the *k*-th epoch. Note that this assumption does not change the problem. It only requires that the number of subareas coincide with that of epoch.

Based on the flow conservation rule, the outgoing flow exceed the incoming flow by the amount of $r \times t_k$.

So the flow conservation rule for each sensor node i at each epoch can be formulated as follows:

$$\sum_{\forall j\in V\cup S} F_{ij}^{k} - \sum_{\forall j\in V} F_{ji}^{k} + B_{input}{}_{i}^{k} - B_{output}{}_{i}^{k} + q'_{ik} = rt_k \qquad \forall i,k \qquad (12)$$

Obviously, each sensor node can sends its data to another sensor node, sink node or it can store in its own data buffer memory.

Let $B_{length}{}_{i}^{k}$ be the buffer queue length of node *i* during the *k*-th epoch. Since the buffer is empty at the system initialization we have

$$B_{length}{}_{i}^{0} = 0 \qquad (13)$$

During each epoch queue length is the sum of queue length in the previous epoch and data generated but not transmitted in that epoch. As a result, the queue length at each epoch can be formulated as follows:

$$B_{length}{}_{i}^{k} = B_{length}{}_{i}^{k-1} + B_{input}{}_{i}^{k} - B_{output}{}_{i}^{k} \qquad \forall i,k \quad (14)$$

In which during the *k*-th epoch which last for t_k seconds, sensor *i* generates data with the rate of *r* bits per seconds and transmit q_{ik} of the generated data. Sensor node *i* buffers B_i^k bits of data during the *k*-th epoch .Since we assume that each application has a specific data-tolerance *D*, the queue length at each sensor should not exceed *D*. i.e.:

$$B_{length}{}_{i}^{k} \le D \qquad \forall i,k \qquad (15)$$

Besides, we assume that based on the predefined QoS requirements, at each point of time ρ percent of all sensors should generates data. For *k*-th epoch which last for $t_k$seconds, at least $\rho \times |V|$ of all sensors should generate data with the rate of r bits per seconds. i.e.:

$$\sum_{\forall i\in V} q'_{ik} \le (1-\rho)|V|rt_k \qquad \forall k \qquad (16)$$

Besides, at the end of the last epoch, all sensors should empty their buffer and send all data to the sink node. In other words, for the WSN with T seconds of network lifetime and $|V|$ sensor nodes, at least ρ% of all sensors should generate and transmit data with the rate of r for T seconds.

$$\sum_{\forall k}\sum_{\forall i\in V} q'_{ik} \le (1-\rho)|V|rT \qquad (17)$$

However, each sensor has limited initial energy denoted by E_0 . Total energy consumed for data transmission and reception should not exceed the initial energy. In other words:

$$E_r \sum_{\forall k}\sum_{\forall j\in V} F_{ji}^{k} + \sum_{\forall k}\sum_{\forall j\in V} E_{ij}^{t} F_{ij}^{k} + \sum_{\forall k} E_{is}^{k} F_{ik}^{k} \le E_0 \quad \forall i \quad (18)$$

Where E_r is the energy consumed for receiving a bit of data and E_{ij}^{t} is the energy consumed for sending a bit of data from sensor node *i* to node *j* defined by (1). Besides, E_{is}^{k} energy consumed for sending a bit of data by sensor node *i* to the sink node during the *k*-th epoch defined by (11).

As a result, we can formulate the problem as linear programming formulation as follows:

$$Max\ T = \textstyle\sum_{\forall k} t_k \quad (19)$$
$$s.t$$
$$(12) - (18)$$

The outputs of the above formulations are the network lifetime, sink sojourn time at each subarea, flow assignment for each sensor node at each time epoch, amount of data sent by each node during each time epoch, amount of data which does not send by each sensor node during each time epoch, queue length for each sensor at each time epoch.

V. Correctness Proof and Complexity Analysis

In this section, we give a formal proof that the solution obtained by Linear programming formulation is (1 − ε) optimal and analyze its complexity.

Denote $\{p_1^*, p_2^*, \dots, p_n^*\}$ as the optimal anchor points for the sink mobility, $\{t_1^*, t_2^*, \dots, t_n^*\}$ and $\{R_1^*, R_2^*, \dots, R_n^*\}$ as their corresponding sojourn times and routing respectively which are all unknown. Beside, let $\{p_1, p_2, \dots, p_n\}$ indicates the optimal anchor points (selected subareas) resulted by solving the linear programming formulation and let $\{t_1, t_2, \dots, t_n\}$ and $\{R_1, R_2, \dots, R_n\}$denoted the corresponding sink sojourn time and routing respectively. We also denote the T^* and T as optimum network lifetime and network lifetime resulted by solving the proposed LP.

Theorem. Based on the definition of T^* and T , we have $T \ge (1-\varepsilon)T^*$

Proof. At each time epoch k, instead of using the optimal routing R_k we use R_k^* for the solution resulted by LP which is clearly suboptimal. That is, denoting $\hat{T}$ as the network lifetime for LP under R_k^* for $(1-\epsilon)T$, we have $T \ge \hat{T}$. Then it is only required to show that $\hat{T} \ge (1-\varepsilon)T^*$

Since we use each R_k^* for at least $(1-\varepsilon)t_i^*$ instead of t_i seconds, for each $F_{ij}^{k} \in R_k$ and ${F^*}_{ij}^{k} \in R_k$ we have

$$(1-\varepsilon){F^*}_{ij}^{k} \le F_{ij}^{k} \le {F^*}_{ij}^{k} \qquad (20)$$

Then to prove $\hat{T} \geq (1-\varepsilon)T^*$, we only need to show the total consumed energy at each sensor node does not exceed its initial energy, which is:

The first inequality holds by (6) . Thus the network lifetime for the solution of the LP under R^* is at least $(1-\varepsilon)T^*$. As a consequence, we have $(1-\varepsilon)T^* \leq \hat{T} \leq T \leq T^*$ which completes the proof.■

The number of subareas has great impact on the problem complexity and the number of LPs which needed to be solve. Thus to calculate the problem complexity, we are going to approximate the number of subareas.

The boundaries of each subareas is either an arc of the circle centered at some node i or an arc of the disk A. Since for each sensor node there are $H_i - 1$ (defined by(8)) circles and there is a circle for A there are totally $N = 1 + \sum_{\forall i \in V}(H_i - 1)$ cicles. Based on [20] the total number of subareas M can be upper bounded by:

$$M \leq N^2 - N + 1 \qquad (21)$$

Based on (8) and (21) we have

$$M = O(N^2) = O\left(\left({}^{N}\!/_{\varepsilon}\right)^2\right) \quad (22)$$

It can be easily seen that the number of constraints and variables used in the proposed LP is about $O(|V|^2)$ and $(|V|^3)$. Hence, the problem can be solved in polynomial time [21].

VI. PERFORMANCE STUDY

In this section, we evaluate the proposed method using an extensive numerical study. The parameter values used during the numerical study are listed in table I. To achieve 0.95 optimal solution we set $\epsilon = 0.05$. We investigate three metrics, namely network lifetime, sink sojourn time distribution and sensors buffer queue length. In order to study our approach for different network topologies we take into account three types of network topologies including samples of linear, grid and arbitrary topologies as follows. The symbols definitions are accessible in table I.

The proposed LP is compared with the ones proposed in [10] and [6]. In fact, in [6] the authors proposed a sink placement approach based on a mixed integer linear programming formulation. Since the integer programming formulation is NP-hard, they proposed an efficient heuristic to find out the near optimal sink location. Meanwhile, in [10] authors investigated on joint sink mobility and routing while the set of anchor points for the sink node are constrained to the sensors locations. However, neither [6] nor [10] assumed any sort of QoS provisioning. However, in our approach we consider an upper bound on delay as the QoS requirement.

Table II.

Parameter	Value
r	$50bps$
α	3
e_t	$50\ nj/bit$
E_r	$150\ nj/bit$
ε	0.05
R_c	$40\ m$
E_0	$5\ Jules$

In the line network shown in Fig.1, the distance between each two neighborhoods are selected within [20,40].

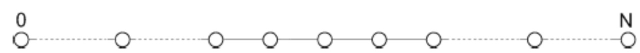

Fig.1 A line network topology

As shown in Table III, using unconstrained mobility (in our approach) can always achieve a higher network lifetime than using a static sink node.

Specially by increasing the size of network, the improvement in network lifetime is more significant. Comparing with the constrained sink mobility (in which the candidate locations for the sink node include only sensor locations) the proposed approach (in which candidate locations for the sink are some discretized subareas) improves the network lifetime.

Besides, it can be seen that if the application can tolerate 200 seconds (i.e., D=200) of delay in data delivery the network lifetime improves about 1.8 in comparison with unconstrained mobile sink with D=0.

Furthermore, by putting only 20% (i.e., ρ=80%) of sensors into sleep mode the network lifetime improves about 2.09 in comparison with the case that $\rho = 100\%$.

An interesting point about the line network topology which is also confirmed in our study and previously observed in [10] is that the improvement network lifetime is

mostly resulted by the substitution effect [10]. That is, the sink node inherits data forwarding load from the neighbor nodes.

As we will show in the next section, for other topologies, the lifetime improvement is caused mostly by load balancing effect rather than substitution effect of mobile sink.

For grid network with $\sqrt{|v|} \times \sqrt{|v|}$ lattices, the average network lifetime achieved for 100 random generated topologies are shown in Tables III.

As followed from the table, for large scale networks, using the static sink node cause unbalance energy consumption resulting a short network life time. However, as the network size increases, the improvement on the network lifetime resulted from unconstrained sink mobility increases.

Using a mobile sink node in grid network improves the network lifetime not only by the load balancing effect but also by the substitution effect. Because of that, the unconstrained sink mobility improves the network lifetime about 2.3 times while D=0 and $= 100\%$.

However, in delay tolerant applications when 200 seconds of delay is tolerable using the mobile sink improves the network lifetime about 2.6. Besides, using at least 80% of sensors at each point of time improves the network lifetime by 3.1. Furthermore, when 200 seconds of delay in data delivery is tolerable and at least 80% of all sensors are active at each point of time the network lifetime improves by 3.78.

In some applications the required accuracy level can be fulfilled by using only a part of sensor nodes instead of using all sensors. Thus, only subsets of sensors are selected as active sensors at each point of time.

As a result, sensors do not gather data from their surrounding area with a same rate in these kinds of applications. Fig.2 shows the normalized rate of not generated data while D=0 and ρ=80% for N=49. The sink node tends to dwells mostly in the center of the target field.

Therefore, sensor nodes which are far from the sink node gather data from their surrounding are with a lower rate than sensors which are located in the center of the field.

We also consider network with N=49,D=200 and ρ=80% . Fig.2 shows the sensors buffer queue length of such a network. Considering Fig.2 and Fig.3 shows that sensors which are far from the sink node (i.e., mostly located around the target field) tends to generate data with a lower rate while the nearby ones have more data in their buffer queue.

We also perform the proposed method on arbitrary network topology (i.e., sensor nodes are deployed based on the uniform distribution on the target field).

Fig.4 shows the average network lifetime over 100 random generated topologies for different scenarios while network size varies from 50 to120 and D=0. Clearly, the network lifetime improves by decreasing the level of accuracy.

In critical application with high accuracy requirement one can use $= 100\%$. However, using $\rho = 90\%$ and $\rho = 80\%$ improve the network lifetime by about 16% and 28% respectively.

Fig.5 illustrates the comparison of network lifetime achieved by different scenarios. For real-time applications we can use $D = 0$. However, when the $D = 200$ seconds is tolerable by application the network lifetime improve by 0.25. Moreover, using $D = 400$ and $D = 600$ improves the network lifetime by about 0.35 and 0.55 respectively.

Table III. Network lifetime resulted by different methods in linear topology

$\lvert V \rvert$	Network Lifetime					
			Proposed method (Unconstrained mobile sink)			
	Static sink placement [6]	Constrained mobile sink [10]	(D=0,ρ=100%)	(D=200,ρ=100%)	(D=0,ρ=80%)	(D=200,ρ=80%)
20	345.76	386.20	458.12	624.72	723.76	918.82
40	726.096	811.02	958.4467	1309.151	1437.67	1103.666
60	1510.28	1686.922	1993.569	2723.034	2990.354	2295.625
80	3141.382	3508.797	4146.624	5663.911	6219.936	4774.9

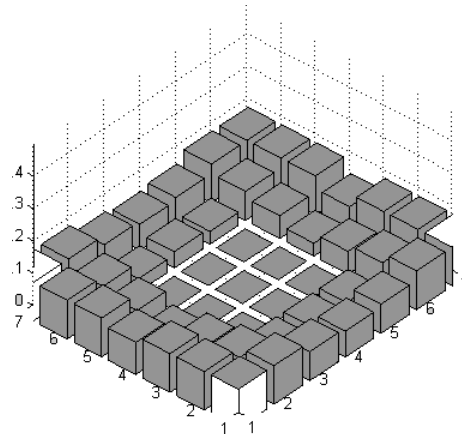

Fig.2 Normalized rate of not generated data for a network with N=49,D=0 and $\rho = 80\%$

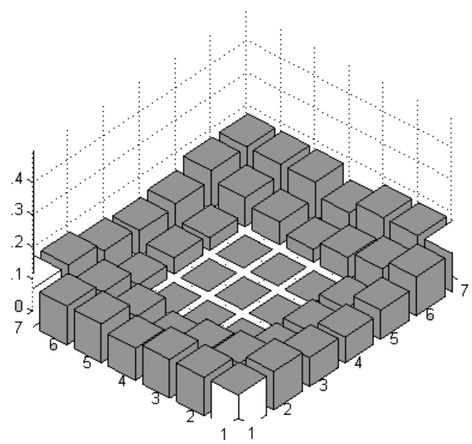

Fig.3 Average Buffer queue length for a network with N=49, D=0 and $\rho = 80\%$

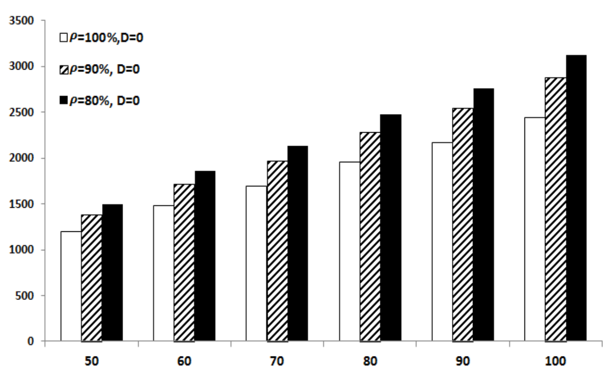

Fig.4 Impact of network size and level of accuracy on the network lifetime

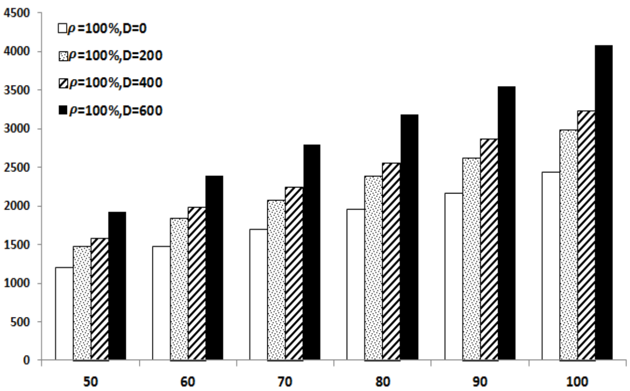

Fig.5 Impact of network size and level of delay-tolerant on the network lifetime

VII. CONCLUSION

In this paper, we present a new framework to achieve the maximum network lifetime for different kinds of application with particular QoS requirements. We exploit joint sink mobility and routing to maximize the network lifetime while QoS requirements are considered as well. For the purpose of QoS provisioning, we consider two metrics:

a) Accuracy level: what percent of sensor nodes are required to be in active mode at each point of time based on the application in-hand.

b) Handling the delay: How much data delivery to the sink node is tolerable? In delay tolerance application each sensor node can postpone its data transmission until the sink node is closed enough. However, in uncritical application with low accuracy level requirement, only a subset of sensors could be used to improve the network lifetime.

For sink mobility model, we used an unconstrained sink mobility to achieve $(1-\varepsilon)$ optimal solution. In fact, for $(1-\varepsilon)$ optimality, the target region can be discretized into a set of subareas, each having a specific transmission cost. Problem formulated based on the linear programming formulation with the respect of predefined QoS requirements.

Besides, the correctness and complexity analysis presented which proves the $(1-\varepsilon)$ optimality of the solution resulted by solving the proposed LP. More important, we prove that the proposed solution can be solved in polynomial time.

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